

Efficiency of Hospitals in Victoria under Casemix Funding: A Stochastic Frontier Approach

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ABSTRACT

This paper estimates the cost frontier for large Victorian public hospitals using the econometric technique of stochastic frontier regression. An estimate of the mean level of hospital cost inefficiency in 1994/95 is obtained, in the period following the introduction of casemix funding. One of the major goals of Victoria's casemix funding system introduced in 1993 was to promote efficiency, hence hospital efficiency under the new system is of interest. We might expect to find a low level of cost inefficiency under a casemix funding system. The cost frontier is estimated by the econometric technique of stochastic frontier regression, which is the preferred efficiency measurement technique as it allows for data errors. The application of frontier models allowed us to estimate the degree of random and non-random efficiency variation across hospitals. Inpatient output is found to explain the majority of inter-hospital variation in total cost. The average level of cost inefficiency in total operating expenditure is estimated to be around 3 percent, using an exponential distribution for the inefficiency component. Where there are differences in costs between hospitals, they appear to be related to administrative, medical support and hotel labour inputs.

Keywords – hospital, efficiency, cost function, stochastic frontier

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1 Introduction

In 1993 the State of Victoria introduced a new system of case mix funding for hospitals. One of the aims of the new output-based reimbursement system was to improve the efficiency of the existing global budget system. It was argued that funding hospitals on the basis of output (casemix) would lead to lower costs for a given level of acute health care.

Casemix funding systems are built on and reinforce incentives for technical efficiency. Paying hospitals on the basis of case mix adjusted episodes of treatment is expected to increase case mix adjusted activity for a given level of inputs. Paying hospitals on the basis of a “benchmark case” provides an incentive to choose inputs that minimize costs. In Victoria the base payment price was based on a benchmark efficiency level. Hospitals with less than benchmark cost-efficient management of a patient group would be forced to reduce costs for a given level of output, since the price paid per unit of output is designed to meet only efficient operating costs.

Optimum reimbursement requires estimation of an efficient price per unit of output. A possible approach in this context would be to adopt a benchmark price based on the lowest cost for each casemix adjusted episode in the state. This approach does not recognise the variability in cost related to exogenous factors and random variation. A more sophisticated approach would be to estimate the degree of avoidable inefficiency, and to fund on the basis of actual marginal cost adjusted for that avoidable inefficiency. Recent advances in the application of frontier models of cost functions have allowed us to estimate the degree of random and non-random efficiency variation across producers. The purpose of this paper is to apply a stochastic cost frontier approach to the estimation of the relative efficiency of Victorian public hospitals in the period following the introduction of case mix funding.

Stochastic Frontier Analysis

The traditional empirical analysis of cost functions in hospitals (Butler 1995, Scott and Parkin 1995, Grannemann et al. 1986, Cowing and Holtmann 1983, Lave, Lave and Silverman 1972 and Feldstein 1967) has focused on the ‘average’ level of costs that best fits the data. These cost functions, estimated by regression analysis, do not trace out a minimum cost locus and are inconsistent with the theoretical concept of the cost function. In contrast the stochastic frontier approach interprets the difference between the intercept term of the cost frontier and that of the usual regression method, as determined by cost inefficiency. The estimated slope coefficients of the cost frontier provide information about the relationship between outputs and costs.

The modern literature on efficiency measurement begins with Farrell (1957). This paper applies stochastic frontier estimation technique (Aigner, Lovell and Schmidt (1977)) to derive the parameters of the cost function and the average level of cost inefficiency for Victorian hospitals. The stochastic cost frontier approach has been applied to United States hospitals in Zuckerman et al (1994) and Vitaliano and Toren (1996). These studies have estimated the average level of cost inefficiency to be around 18%.

The traditional analysis of cost function for hospitals has focussed on issues of the existence and size of economies of scale and scope. The focus of this paper is on the determinants of efficiency, but the stochastic frontier model can be used to estimate the extent of returns to scale in a multi-product setting. We measure the determinants of costs and the extent of inefficiency using a translog and Cobb-Douglas cost function with multiple outputs. This allows consideration of the extent of economies of scale.

The paper is organised as follows: Section 2 lays out the general framework of the application of the stochastic frontier approach to the cost function. Empirical issues, model specification and data are reviewed in Section 3. Section 4 presents our results. We conclude with a discussion of the implications of the analysis for the measurement of efficiency in hospitals.

2. Empirical Issues

2.1 Model Specification

The functional form may be made flexible so that it can represent any relationship between costs, outputs and input prices. The translog form is the most commonly used and preferred flexible functional form for cost functions. However, the chief advantage of the translog form arises from its joint estimation with input share equations. Its value as a single equation model is limited because of collinearity among its many terms (Vitaliano and Toren (1994)). The increased flexibility given by the higher order terms is gained at the cost of the number of parameters to be estimated. The translog is also not well suited to the use of a large number of disaggregated output categories, since the requirement of positive levels of all outputs is not likely to be met.

This paper attempts to estimate a translog model but difficulties with the translog model (frontier estimates could not be obtained or implausibly signed coefficients were produced) make it unsuitable for frontier estimation in the analysis in this paper. It is useful to test the restriction that the translog model reduces to the Cobb-Douglas, i.e. the squared outputs, input price and output-input price cross-product terms are all statistically insignificant. The F-statistic is used to test the restrictions that the higher order and cross-product terms in the translog form, take the value zero.

The reported results use the theoretical multiproduct cost function estimated in Cobb-Douglas form:

$$\log TC = \alpha_0 + \sum_{j=1}^l \alpha_j \log Y_j + \sum_{k=1}^m \beta_k \log W_k \quad (1)$$

where Y is the vector of output and W_k is the vector of input prices. However, note that the number of terms are reduced by assuming restrictions of non-jointness i.e. no economies of scope, and input-output separability.

The data and previous studies suggest two possible measures of total cost, depending on whether the interest is in the inpatient activities or overall activities of a hospital. The first measure available is Admitted Inpatient Expenditure (AIE), which can be used if the focus is on hospital inpatient care. Total Operating Expenditure (TOE) is the wider measure of hospital cost and consists of AIE and costs of other types of care. The main difference between using these two measures is that TOE includes expenditure on outpatient activities, hence using TOE implies that output measures for these other hospital activities such as outpatient and emergency services should be included in the cost equation. The correlation between TOE and AIE is calculated to be high, hence the choice of measure of total cost is not expected to affect the results substantially. Both measures of total cost are used in the initial analysis, to compare results across both models.

The cost function is chosen for the analysis here as hospital output and input prices are expected to be exogenous, and input quantities endogenous. Outputs of hospitals are exogenous if the

demands of the population served by a hospital, determines the level of output. The specification of exogenous output variables assumed to be uncorrelated with the disturbances, is tested. Input prices are exogenous under national wage bargaining or competitive factor market assumptions, which is a reasonable assumption in most markets for hospital factors of production. Aggregated cost data rather than input quantities are also easier to obtain. The use of total cost as the dependent variable in a cost function requires only a single equation to be estimated, compared to the use of outputs as dependent variables. The cost function approach has been widely used to model the technology of firms operating in regulated environments.

The RESET test is used to generally test the functional form, by adding higher orders of the fitted values of the dependent variable to the regression and testing the statistical significance of these fitted values.

Although estimation of a total rather than an average cost function is preferred, the total cost formulation may be less likely to fulfil the OLS regression assumption of homoscedasticity. In this paper, the Breusch-Pagan (1979) test is used to test the null hypothesis of homoscedasticity.

2.2 Data

This paper uses data on Victorian public hospitals. Table 1 presents the descriptive statistics of all the variables used in the estimation of the stochastic frontier cost function.

There are over 130 Victorian public hospitals in 1994/95, but only major Victorian hospitals are selected for the analysis in this paper. Smaller hospitals are expected to have very different characteristics from large hospitals, which are difficult to control for, and can cause results and estimates of inefficiency to be biased. Selecting the major hospitals which are defined as the two groups of largest hospitals ie. Group A and B, and eliminating hospitals with insufficient data, results in a sample of 35 hospitals for analysis. This sample of hospitals represents 86.5% of acute separations and 80% of acute treatment bed-days in all Victorian public hospitals.

Output

There are a number of possible measures of hospital inpatient output in the literature and units commonly adopted are the number of cases treated and bed-days. A case mix adjusted measure of activity, Weighted Inlier Equivalent Separations (WIES), is used as the measure of output. WIES is the sum of all discharges adjusted for variability (Inlier Equivalent Separations), weighted by a DRG specific case weight based on the relative cost of the DRG in a sample of Victorian hospitals. WIES is the basic unit for variable payments which form part of the payment formula for Victorian hospitals (Duckett (1995)).

WIES is preferred as the hospital inpatient output measure rather than acute treatment bed-days, as it uses acute separations as the basic unit of output and adjusts for the mix of case severity. Bed-days is a commonly used crude measure of the complexity of cases. WIES on the other

hand is a measure of casemix weighted separations, adjusted for outlier lengths of stay. Only one of these two measures is used, to avoid collinearity problems.

Using WIES means that one explanatory variable is used to measure both the volume and case mix of inpatient hospital output. This is parsimonious in the number of estimated parameters. The Cobb-Douglas cost equation estimated for inpatient care, is

$$AI = \alpha_0 + \alpha_1 WI + \sum_{k=1}^m \beta_k \log W_k + v + u \quad (2)$$

where AI and WI are the logs of AIE and WIES respectively.

When Total Operating Expenditure (TOE) is used as the measure of total cost, measures of outpatient activities which parallels those used in the literature, are also used. The Cobb-Douglas form of the cost equation estimated is

$$TO = \alpha_0 + \alpha_1 WI + \alpha_2 OCOS + \alpha_3 EOS + \sum_{k=1}^m \beta_k \log W_k + v + u \quad (3)$$

where TO is the log of TOE, OCOS is the log of On Campus Medical/Clinical Occasions of Service and EOS is the log of Emergency/Casualty Occasions of Service, using measures of emergency and outpatient visits.

Given the inherent limitations of measuring and controlling for hospital output in the cost function, especially those related to quality, some of what is observed as cost inefficiency may still be unmeasured output differences across hospitals. It is desirable to account for variations to the extent possible, in the quality of care between hospitals. Previous studies have used measures of output quality and patient outcomes in the cost function, but the results have not been sensitive to these types of variables.

Data on commonly used measures of quality of care such as the expected 30-day mortality rates and expected in-hospital complications (Zuckerman et al. (1994)) are difficult to obtain at an individual hospital level for this analysis. Available data on proxies for quality of care such as nurses per bed and an indicator of re-admissions, were used but were found to be poor quality measures i.e. implausible results and failure to obtain frontier results. Thus, quality measures have been omitted from the reported results of the analysis.

Input Prices

Data available on the types of staff employed in large hospitals are described in Table 1. It appears that the salaries of all categories of labour except medical staff, are highly correlated, with a correlation coefficient above 0.99. Therefore, it is not considered necessary to include all the categories of labour in the cost regression. This also avoids collinearity problems. Zuckerman et al. (1994) used an instrumental variable to replace the endogenous average annual salary per full-time equivalent employee as the price of labour. The salary for each individual staff category such as nursing salary is set under collective bargaining or competitive factor market

assumptions in Victoria. The average salary for each staff category is not expected to vary with changes in the number and skill-mix of employees, hence it is assumed to be exogenous.

Capital-related data available such as depreciation and interest are not considered good estimates of the price of capital as Victorian public hospitals do not own their buildings and assets are generally not depreciated in public hospital accounting systems. Interest is not usually paid by public hospitals, as funds are generally provided by Governments as 'free equity'. Since data on better measures such as the rental price of land are not available, capital input price has been omitted from the analysis. In fact variation in the cost of capital is not likely to explain much of the variation in recurrent expenditure between hospitals.

Dummy Variables

In Australia, large teaching hospitals are concentrated in metropolitan areas, and the available data group hospitals according to teaching and number of separations. Teaching hospitals typically perform more complex, innovative or rare procedures that may not be captured by the volume or case-mix variables. Two approaches have been taken in the literature to allow costs to be different in different types of hospitals. Dummy variables can be used (Vitaliano and Toren (1996)) or the overall sample can be partitioned as in Zuckerman et al. (1994). This paper prefers the use of dummy variables, since the sample size of all Victorian teaching hospitals is quite small. Variation in costs across different groups of hospitals are accounted for by the use of dummy variables as follows:

$$\log TC = \alpha_0 + \sum_{j=1}^l \alpha_j \log Y_j + \sum_{k=1}^m \beta_k \log W_k + TCH + AONE + v + u \quad (4)$$

where TCH is a dummy variable which takes the value one for group A teaching hospitals and AONE takes the value one for group A1 hospitals, which is the group of large teaching hospitals

3. Results

3.1 Ordinary Least Squares Results

Two sets of results are analysed: the inpatient model with total cost measured by Admitted Inpatient Expenditure and the overall model with total cost measured by Total Operating Expenditure. The overall model is preferred to the inpatient model as it appears to fit the data better on the basis of the adjusted R^2 , and only the results from the overall model are reported. It is more likely that inpatient activities are produced jointly with outpatient activities, hence the data on Total Operating Expenditure are likely to be more accurate since there may be difficulties in allocating costs to inpatients.

The ordinary least squares results estimated using the LIMDEP program (Greene (1993)), using TO as the dependent variable, are reported in Table 2. WIES, outpatient and emergency visits are used as output variables. 'T-ratio' is the test statistic for individual statistical significance.

Hospitals with no emergency occasions of service are omitted, since implausible results i.e. negative output coefficients, are obtained with the full sample.

Labor input prices are primarily selected from the available data set according to the performance of their results. As disaggregated data on labor input prices are available, a few categories of staff have been chosen. Various combinations of labor input prices were experimented with in the analysis but use of certain labor input price specifications do not allow frontier results to be obtained. The best specification of labor input prices uses medical salary, which consistently has a theoretically plausible positive coefficient. Hence, the preferred specification for the cost frontier regression is:

$$TO = \alpha_0 + \alpha_1 WI + \alpha_2 OCOS + \alpha_3 EOS + \beta_1 MWAG + TCH + AONE + v + u \quad (5)$$

where MWAG is the log of MWAGE. The specification with one wage variable is preferred as the adjusted R^2 is higher.

Interpretation of results

The coefficient on the output measure WIES is positive, and highly significant. The coefficients on the other output variables EOS and OCOS are positive. This is consistent with the theoretical model which suggests that higher levels of output increase costs while holding input prices fixed. However, the magnitude of the coefficients on EOS and OCOS are very small and they are statistically insignificant, indicating that the marginal costs of emergency and outpatient visits are negligible compared to the marginal cost of WIES. The elasticity of cost with respect to WIES is 0.88.

The relationship between cost and revenue which is paid on the basis of WIES is found to be weak, thus there is not expected to be perfect collinearity between cost and WIES, although WIES is based on clinical costing studies of Victorian hospitals. Examining the data on the 35 hospitals' net deficit or surplus in 1994/95, the standard deviation is large relative to the mean deficit. In addition, the proportion of payments by fixed grants dominates the proportion of funding by variable payments per WIES in most hospitals. Therefore, revenue is not solely paid on a per WIES basis, and this weakens the relationship between revenue and WIES.

The coefficient on MWAGE is positive, theory indicates that increased input prices raise costs given specified levels of output. Labor input prices are never found to be statistically significant. This is expected since the variation in input prices is small, as shown in Table 1.

The statistically insignificant but positive coefficient on the TCH variable indicates that smaller teaching (A2) hospitals do not have significantly higher costs than non-teaching (B) hospitals. The AONE variable is positive and is always statistically significant, indicating that large teaching (A1) hospitals have significantly higher costs than small teaching hospitals. The results also suggest that the difference between the costs of large teaching hospitals and non-teaching hospitals, is statistically significant, the sum of the coefficients on AONE and TCH indicate the difference in

costs between these two groups of hospitals. Therefore, large teaching hospitals have significantly higher costs than the rest of the hospitals in the sample.

The sum of the coefficients on the output variables estimates the elasticity of scale. The sum of the output coefficients is around 0.90 in the overall model in Table 2, indicating some evidence of economies of scale in the overall activities of a Victorian public hospital, which can be contrasted with a 1.11 sum of the coefficients on the three output variables in Vitaliano and Toren (1996).

Econometric Issues

It is found that the use of a Cobb-Douglas model in this paper appears appropriate, hence we use a Cobb-Douglas model in the analysis. The null hypothesis of non-zero higher order and cross-product terms is rejected, using the F-statistic.

The null hypothesis of homoscedasticity cannot be rejected, using the Breusch-Pagan test. Hence, the OLS models are not adjusted for heteroscedasticity.

It is found that the coefficients on the fitted values are statistically insignificant using the RESET test, indicating that the hypothesis that the disturbance term has a conditional mean of zero cannot be rejected. Hence the OLS models do not appear to suffer from the omitted variables problem.

It is found that WIES is exogenous in the OLS equation, and the assumption of exogenous hospital inpatient output in the cost function, is reasonable.¹ Similarly, emergency and outpatient visits were also found to be exogenous. Therefore, it can be concluded that the cost function assumption of exogenous output is reasonable.

3.2 Frontier Estimation

The normal distribution is assumed for the random error term v , and the half-normal distribution is commonly assumed for the one-sided error term u . The cost frontier is estimated using three distributional assumptions for the one-sided error term i.e. half-normal which is truncated at zero, truncated normal which is truncated at a non-zero point, and exponential. The increased complexity of the gamma distribution excludes its use in this paper. If the results in this paper are little affected by the use of different distributions for u , this may suggest that the use of an arbitrary distribution for the one-sided error component, is not a strong assumption to make.

The results assuming a half-normal distribution for the asymmetric error term (u), are reported in Table 2. Z-values are 'asymptotic t ratios' used to test individual statistical significance of Maximum Likelihood estimates, and are asymptotically distributed as $N(0,1)$ under the null hypothesis that the associated coefficient is zero. Z-values are reported for the stochastic frontier maximum-likelihood estimates, but statistical inferences in this paper are based on the OLS estimates. The z-values can only be used as test statistics in larger samples.

The residuals ($E(u/v+u)$) derived according to the formula by Jondrow et al. (1982), are estimates of the one-sided error term (u). For the half-normal model, the residual is computed by the following formula

$$E[u | \varepsilon] = \sigma\lambda / (1 + \lambda^2) [\phi(\varepsilon\lambda/\sigma) / \{1 - \Phi(\varepsilon\lambda/\sigma)\} - \varepsilon\lambda/\sigma] \quad (6)$$

where $\lambda = \sigma_u/\sigma_v$

ϕ is the probability density function of the standard normal and Φ is the cumulative density function.

OLS results are always presented alongside frontier results to ease comparison of the estimates from these two models, and statistical inferences are based only on the OLS model. The magnitude of the OLS and frontier slope coefficients appear to be mostly the same. The frontier intercept is below the OLS intercept, which is as expected.

$(\sqrt{\sigma_v^2 + \sigma_u^2})$ is the standard deviation of the composed error term. (σ_u/σ_v) indicates the relative variation in the one-sided error term, compared to the symmetric random error component. In this case, since the symmetric component dominates the asymmetric component, it appears that the one-sided error component is not significant. The finding in this paper that σ_u^2 is fairly small suggests that the frontier model is close to the usual regression model. If $u = 0$, then the OLS estimates in the frontier and the cost function fulfills the assumption of cost minimization, and there is no difference between the frontier model and OLS. The distinction between the frontier model and the usual regression model is the one-sided error u . Variation in the frontier across hospitals appears to be attributed only to random error. Looking at the estimates of the parameters of the distributions of the disturbances such as σ_u^2 and σ_v^2 , the conclusion that the asymmetric component is dominated by the symmetric component, is confirmed. The variation of the symmetric component is around three times larger than the variation of the asymmetric component. The picture that emerges is one of little variation of observed cost above the frontier.

The estimated mean of the residuals or one-sided error terms, is 4.6%. The ratio of actual to least cost for this logarithmic specification may be written as

$$C(Y,W) e^{v+u} / C(Y,W) e^v = e^u$$

$e^{0.046}$ is 1.0471, which translates into average mean inefficiency of 4.71%.

Assuming a truncated normal distribution for the one-sided error term, the magnitude of the coefficients is almost the same as the OLS coefficients. μ/σ_u is very small, hence the distribution of u is centered close to zero, suggesting that the truncated normal model reduces to the half-normal model. The mean of u is 4.6%.

The results from assuming an exponential distribution for u , are reported in Table 3. For the exponential model

$$E[u | \varepsilon] = z + \sigma_v \phi(z/\sigma_v) / \Phi(z/\sigma_v) \quad (7)$$

where $z = \varepsilon - \theta \sigma_v^2$

and θ is the distribution parameter.

The magnitude of the frontier coefficients on WI, OCOS, MWAGE, TCH and AONE is the same as the OLS coefficients, whilst the frontier coefficient on EOS is close to the corresponding OLS coefficient. The frontier intercept is still lower than the OLS intercept as expected, although the difference between the two intercepts is smaller, this could be due to the smaller variation of the asymmetric component.

The difference between the variation of the two error components is greater than in the half-normal case. Mean u is 2.7%, and $e^{0.027}$ is 1.0274. This translates into mean average inefficiency of 2.74%, which is lower than the estimate from the half-normal distribution of u .

In this paper, the estimated mean inefficiency is lower in the exponential model than in the half-normal model. Empirical examples in the literature found differences in the measures of efficiency across different distributions of u . Hence, the estimates of cost inefficiency appear to be sensitive to the assumption about the distribution of u . There is no clear specification test to guide the selection between the alternative distributions for the one-sided error term.

The inefficiency estimates from all three distributions used in this paper are also highly correlated, suggesting that the choice of the distribution of the one-sided error term does not affect the results substantially. In the analysis in this study, use of the exponential distribution of the one-sided error component produces a slightly higher log likelihood than the half-normal case, suggesting a better fit by the exponential distribution. Selecting the model with the lowest variance of the composed error (Vitaliano and Toren (1996)) also indicates that the exponential model fits the data best. Therefore, the use of the exponential distribution for the one-sided error component is preferred over the half-normal distribution. The preferred cost frontier regression with TO as the dependent variable and WI, OCOS, EOS, MWAGE, TCH and AONE as explanatory variables, has an exponential distribution for the one-sided error term.

For the overall model, mean cost inefficiency ranges from 2.7 percent in the exponential model to 4.7 percent when the other distributions are assumed for the asymmetric error component. This range of estimates suggests the cost frontier for the hospitals in this sample is not very far below the average actual cost as estimated by OLS regression.

The estimated mean cost inefficiency for these Victorian public hospitals are lower than the estimates of the average level of inefficiency in United States hospitals. For example, Zuckerman et al. observed mean inefficiency of 13.4% of total costs, when a set of hospital-level variables is used to control for output heterogeneity, and 18.8%, when costs were treated solely as a function of output volume and input prices. Vitaliano and Toren (1994) had an estimate of around 18% inefficiency. The results are not directly comparable however since considerable differences in

the hospitals sampled and model specifications, may be responsible for the differences between the results here and in previous studies.

3.3 Factors Affecting Efficiency

The residuals or estimates of the one-sided error terms obtained from the estimation of the cost frontier are used as the dependent variable in a regression on a number of explanatory variables. The choice of explanatory variables to be used in this second stage regression, is guided by the literature and data availability. Descriptions of the variables used are reported in Table 4. Only three types of variables are examined in this paper i.e. occupancy rates, hospital size, and input use per unit of output. Estimates of u from the preferred cost frontier regression (equation (5)) are used as the dependent variable in the first analysis.

As the estimate of u cannot take a negative value and the data are censored below 0, the Tobit model estimated by Maximum Likelihood estimation is also used, as suggested by Dor (1994). It is noted that OLS estimates tend to be biased toward zero compared to the Maximum Likelihood (Tobit) estimator. However, these estimates are compared to the results in previous stochastic frontier literature, which used OLS estimates.

i) Occupancy (OCC)

The mean occupancy rate for the hospitals in the sample is 79.46%. Hospital occupancy rates are expected to be inversely related to inefficiency.

The coefficient on OCC is negative and marginally statistically significant. Although the estimated result suggests that an increase in occupancy would reduce inefficiency, the magnitude of this effect is small. The OLS results imply that a 10% increase in occupancy rates would reduce inefficiency by only 0.2%. In contrast, Zuckerman et al. (1994) found that a 10% increase in occupancy rates would reduce inefficiency by around 2%.

ii) Size (SIZ)

The number of beds is positively related to inefficiency. However, the elasticity of inefficiency with respect to the number of beds is very small, and SIZ is statistically insignificant. Therefore, this result is in contrast with the findings in some previous studies such as Zuckerman et al. (1994) that the number of beds was significantly negatively related to inefficiency. However, the statistical insignificance of this coefficient suggests that little emphasis can be placed on this result.

iii) Input Use (Medical staff per WIES)

Hospital inefficiency is expected to increase with the number of staff per unit of WIES. Hospitals that are overstaffed relative to their outputs probably are not operating at the most efficient configuration.

The coefficient on Medical staff per WIES is very small, statistically insignificant and negative, which implies that inefficiency decreases when the use of medical staff relative to outputs increases. This result is unexpected, and conflicts with the results from previous studies such as

Zuckerman et al. (1994)'s finding that a 1 percent increase in FTEs per adjusted admission was associated with a 0.4 percent increase in inefficiency, suggesting that other staff categories should be examined. However, only the individual staff categories which were used in estimating the cost frontier can be used in the second stage regression. Hence, residuals that can be obtained from other plausible wage specifications for the cost frontier are used to empirically analyze what other staff categories may be related to inefficiency.

Using MWAGE and ACWAGE together in the cost frontier produces plausible frontier results, hence the residuals from this specification are used. Estimates of u from the frontier regression with TO as the dependent variable and WI, OCOS, EOS, MWAGE, ACWAGE, TCH and AONE as explanatory variables, using the exponential distribution for the one-sided error term, are then used as the dependent variable in the second stage regression.

Although the magnitude of the coefficient on occupancy is the same as in the first analysis, occupancy is now statistically insignificant. The magnitude of the coefficient on size is smaller when this specification is used. The coefficient on Medical staff per WIES is also smaller but still negative.

Administration and Clerical staff per WIES is the only statistically significant variable. A 1% increase in EFT Administration and Clerical staff per WIES is associated with a 0.02% increase in inefficiency.

When specifications with other categories of staff are used, Medical Support staff per WIES and Hotel and allied staff per WIES are found to be the only other staff categories that are significantly related to inefficiency. Examining the correlations between Administration staff per WIES, Medical support staff per WIES and Hotel staff per WIES, the results are not surprising as the input use per WIES of these staff categories are found to be highly correlated.

3.4 Efficiency Grouping

An empirical issue examined in the literature is whether hospitals found to be more or less efficient using the stochastic frontier approach, are teaching hospitals, or have different case-mix, compared to the other groups of hospitals (Zuckerman et al. (1994)). Zuckerman et al. also examined whether more efficient hospitals are rewarded. Vitaliano and Toren (1996) examined whether small size means higher variability in cost and inefficiency.

Examination of individual hospital inefficiency estimates reveals that non-teaching hospitals have outlier values of the estimated asymmetric error component. Unfortunately, no clear cut patterns can be observed from comparisons of variables such as size, as compared to multiple regression techniques.

It is found that the most efficient group of hospitals does not have substantially different proportion of teaching hospitals, case-mix index and case-mix adjusted length of stay, compared to the other groups of hospitals. The least efficient group of hospitals is found to have

substantially higher deficits than the most efficient group, although the rankings are not consistent with expectations.

4. Conclusion

We might expect to find a low level of cost inefficiency under a case mix funding system. Since the introduction of casemix funding in Victoria, there have been reports of a significant reduction in urgent waiting lists and an increased level of activity in terms of treated cases per bed, at the same time as a significant reduction in expenditure (Duckett 1995). The overall number of patients treated in Victorian hospitals in the period July-December 1993 was about 5% higher than the number treated in the same period in 1992. Total expenditure in hospitals in Victoria was about 5% less than in 1993/94 compared to 1992/93. The number of casemix adjusted separations increased by 4.4%.

Using a stochastic cost function with an exponential distribution for the one-sided error component, we have estimated the mean cost inefficiency in total operating expenditure for large Victorian public hospitals to be around 3 percent. Assuming other distributions for the asymmetric error component only raises mean inefficiency to less than 5 percent. Hence it appears that these results are quite consistent with the expectation that casemix funding is providing hospitals with appropriate incentives for cost efficiency. With total operating expenditure of all acute hospitals at \$2,673.15 million, even this low level of estimated inefficiency implies potential savings of approximately \$70 million per year. The results are robust with respect to differences in the specification of the cost function. The symmetric component of the composed error term in the model was found to dominate the one-sided component. This suggests that the use of the stochastic frontier model will produce similar parameter estimates to the OLS model. The implication is that there are low levels of cost inefficiency. The general conclusion is that it appears that Victorian hospitals do not have a high level of relative cost inefficiency, especially when compared to previous inefficiency estimates of United States hospitals and other health care institutions. This is consistent with the expectation that casemix funding is providing hospitals with appropriate incentives for cost efficiency, although we cannot be sure of a causal connection since we do not have any comparative data from other funding systems in Victoria or comparative data prior to 1993.

Where there are differences in costs between hospitals, they appear to be related to administrative medical support and hotel labour inputs. This implies that there may be some scope for hospitals to improve their cost efficiency by changing the mix of staff. However the study has not been able to measure some important aspects of output such as the quality of care and so any conclusions that might be made about relative efficiency need to be interpreted with caution. This is particularly true if some types of staff who contribute to the higher cost of individual hospitals also provide aspects of care which contribute to quality rather than throughput. Unfortunately no appropriate measure of the quality of care was available in this data set. For that reason, observed inefficiency may be the result of unmeasured output differences across hospitals. This limits our ability to determine the contributing factors to inefficiency but it does suggest that if anything cost inefficiency as a whole is likely to be lower than that estimated.

There are a number of other interesting implications of the results. Teaching hospitals have a significantly higher level of costs than other hospitals since they treat cases with a higher

complexity. There is also some evidence that hospitals occupancy rates are inversely related to inefficiency. The data also suggest that there are economies of scale, but not of a high degree. We were not able to consider the extent of economies of scope using the Cobb-Douglas cost function and difficulties with the translog model made it unsuitable for frontier estimation in our analysis.

The stochastic cost frontier estimates the determinants of a variation in expenditure across hospital within a common system of payment per casemix adjusted episode. It is not surprising therefore that the casemix variable WIES explains a great deal of the variation in hospital expenditure and that other input variables are not significant. This limits our ability to look at the determinants of inefficiency in Victorian hospitals, but it does not lead to biased estimates of global inefficiency. Another possible explanation for the importance of WIES as an explanatory variable is that hospital expenditure is in part determined by government payment, which in turn is based on benchmark costs and targets for individual hospital throughput. It might be argued that in this situation a stochastic estimation technique is inappropriate and a non-stochastic approach such as data envelopment analysis would be more suited. However, hospitals do run surpluses, run over target, and casemix payment on average meets only about 40% of their total annual expenditure. In our view there is sufficient discretion on the part of hospital management to argue that this is not a fully deterministic relationship and that frontier analysis is an appropriate technique.

In terms of implication of this paper for hospital reimbursement rates, since the paper implies low levels of inefficiency across hospitals at the current level of reimbursement there seems little obvious motivation to change reimbursement rates. However this ignores the major difficulty in hospital studies of appropriately measuring hospital output and adjusting for quality (Newhouse 1994). It also assumes that the casemix funding has been a major causal factor in creating a situation of low inefficiency. In fact, the direct incentive effects on clinical management of a global budgeting system such as casemix funding are relatively weak. If casemix funding in Victoria has had any incentive effect on costs it has come about through a dramatic reduction in public expenditure in a short period of time. This makes even more necessary the appropriate measurement of hospital output. Lastly any conclusion that we make about the global inefficiency of the Victorian public hospital system has to recognise that inefficiency measures from stochastic frontier analysis only provide us with relative efficiency measures. That is to say efficiency is only measured relative to the most efficient hospital in the sample. Similarly inefficient hospitals can be ranked as relatively efficient by the stochastic frontier method. It is conceivable that the small variance of the inefficiency component found in this paper may be evidence of similar inefficient behaviour by all hospitals in the sample reflecting a consensus on current medical practice rather than efficient management.

In spite of these caveats it is difficult not to conclude from the evidence presented that Victorian public hospitals are remarkably efficient. While a causal connection with casemix funding has not been firmly established, the system may have led to a convergence of cost minimising behaviour across hospitals.

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APPENDIX

Table 1: Descriptive statistics for 35 group A and B Victorian hospitals for the financial year 1 July 1994 to 30 June 1995

Variable	Description	Mean (standard deviation)
<u>Dependent variables</u>		
AI	Log Admitted Inpatients Expenditure	10.3927 (0.8496)
TO	Log Total Operating Expenditure	10.7022 (0.8371)
<u>Output variables</u>		
WI	Log Weighted Inlier Equivalent Separations	9.5580 (0.7993)
EOS	Log Emergency/Casualty Occasions of Service	9.9263 (1.2072)
OCOS	Log On-Campus Medical/Clinical & Support Occasions of Service	10.8171 (1.2414)
<u>Input price variables</u>		
MWAGE	Log average Medical Salary per E.F.T.	11.4824 (0.2347)
NWAGE	Log average Nursing Salary per E.F.T.	10.6220 (0.0433)
ACWAGE	Log average Administration and Clerical Salary per E.F.T.	10.3763 (0.0586)
HAWAGE	Log average Hotel and Allied Salary per E.F.T.	10.2444 (0.0542)
MSWAGE	Log average Medical Support Salary per E.F.T.	10.5624 (0.0557)
RMOWAGE	Log average R.M.O. Salary per E.F.T.	11.1024 (0.1047)
<u>Dummy variables</u>		
TCH	1 if teaching hospital	0.4595 (0.5052)
AONE	1 if group A1 hospital	0.1622 (0.3737)

Source of data: Rainbow Hospital Indicators (1994/95)

Table 2: Half-normal distribution for the one-sided error term
Cobb-Douglas cost frontier
Dependent variable is TO

Variable	OLS Coefficient	t-ratio	Frontier Coefficient	z-value
<i>Constant</i>	0.76	0.73	0.71	0.50
WI	0.88	15.57**	0.88	10.65
EOS	7.9×10^{-4}	0.04	7.9×10^{-4}	0.01
OCOS	0.01	0.44	0.02	0.35
MWAGE	0.11	1.26	0.11	0.92
TCH	0.04	0.60	0.04	0.45
AONE	0.27	3.80**	0.27	2.14
Log likelihood			28.14	
$\sqrt{\sigma_v^2 + \sigma_u^2}$			0.11	0.87
σ_u / σ_v			0.59	0.19

$\sigma_v^2 = 0.0095$ $\text{Var}[u] = [\pi / 2 - 1] \sigma_u^2 = 0.0019$
 $\sigma_u^2 = 0.0033$ $E[u] = \sqrt{(2/\pi)} \sigma_u = 0.0458$

** p-value ≤ 0.05

Table 3: Exponential distribution for the one-sided error term
Cobb-Douglas cost frontier
Dependent variable is TO

Variable	OLS Coefficient	t-ratio	Frontier Coefficient	z-value
Constant	0.76	0.73	0.73	0.54
WI	0.88	15.57**	0.88	10.77
EOS	7.9×10^{-4}	0.04	8.0×10^{-4}	0.01
OCOS	0.02	0.44	0.02	0.35
MWAGE	0.11	1.26	0.11	0.92
TCH	0.04	0.60	0.04	0.45
AONE	0.27	3.80**	0.27	2.18
Log likelihood			28.15	
θ			36.68	0.13
σ_u/σ_v			0.27	

$$\sigma_v^2 = 0.0099$$

$$\text{Var}[u] = 1/\theta^2 = 0.0007$$

$$\sigma_u^2 = 0.0007$$

$$E[u] = 1/\theta = 0.0273$$

Table 4: **Descriptive statistics of possible sources of inefficiency**
1994/95 data

Variable	Description	Mean (standard deviation)
OCC	Log Occupancy rate	-0.2376 (0.1251)
SIZ	Log Beds available	5.2883 (0.7281)
MW	Log E.F.T. Medical Staff per WIES	-7.2795 (1.4759)
ACW	Log E.F.T. Administrative and Clerical Staff per WIES	-4.9349 (0.2723)
MSWIES	Log E.F.T. Medical Support Staff per WIES	-5.1610 (0.4516)
HAW	Log E.F.T. Hotel and Allied Staff per WIES	-4.6542 (0.2750)

ⁱ When the fitted values from the OLS regression of TO on EOS, COS, MWAGE, TCH and AONE were added to the usual regression, the coefficient on the fitted values is statistically insignificant. This single-equation version of the Hausman test has been devised by Spencer and Berk (1981).